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IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re patent application of:

Applicant(s): Susan T. Dumais, *et al.*

Serial No: 09/850,172

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Examiner: Joseph P. Hirl

Art Unit: 2121

Title: PROBABILISTIC MODELS AND METHOD FOR COMBINING MULTIPLE CONTENT CLASSIFIERS

Mail Stop Appeal Brief – Patents
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APPEAL BRIEF

Dear Sir:

Applicants' representative submits this brief in connection with an appeal of the above-identified patent application. A credit card payment form is filed concurrently herewith in connection with all fees due regarding this appeal brief. In the event any additional fees may be due and/or are not covered by the credit card, the Commissioner is authorized to charge such fees to Deposit Account No. 50-1063 [MSFTP217US].

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I. Real Party in Interest (37 C.F.R. §41.37(c)(1)(i))

The real party in interest in the present appeal is Microsoft Corporation, the assignee of the present application.

II. Related Appeals and Interferences (37 C.F.R. §41.37(c)(1)(ii))

Appellants, appellants' legal representative, and/or the assignee of the present application are not aware of any appeals or interferences which may be related to, will directly affect, or be directly affected by or have a bearing on the Board's decision in the pending appeal.

III. Status of Claims (37 C.F.R. §41.37(c)(1)(iii))

Claim 29 has been withdrawn. Claims 1-28, 30 and 31 stand rejected by the Examiner. The rejection of claims 1-28, 30 and 31 is being appealed.

IV. Status of Amendments (37 C.F.R. §41.37(c)(1)(iv))

Proposed amendments to claims 1, 5, 9, 16 and 18 in Applicants' Reply to Final Office Action have not been entered.

V. Summary of Claimed Subject Matter (37 C.F.R. §41.37(c)(1)(v))

A. Independent Claim 1

Independent claim 1 relates to a computer system for classifying items. (*See e.g.*, p. 4, line 24 - p. 14, line 9, and, Fig. 1). The system includes a computer system component that applies probabilistic dependency models, one for each of a plurality of categories, to an item to provide with respect to each of the plurality of categories an indication of whether the item belongs. (*See e.g.*, p. 4, lines 25 - 29, p. 5, lines 7 - 11, p. 19, lines 21 - 25, p. 20, line 24 - p. 21, line 5, and, Fig. 7). The probabilistic dependency models collectively employ outputs from a plurality of classifiers. (*See e.g.*, p. 6, line 13 - p. 6, line 28). The outputs employed by the probabilistic dependency models vary among the probabilistic dependency models. (*See e.g.*, p. 6, line 29 – p. 7, line 7).

B. Independent Claim 5

Independent claim 5 relates to a computer system for classifying items. (*See e.g.*, p. 4, line 24 - p. 14, line 9, and, Fig. 1). The system includes a computer system component that applies a probabilistic dependency model to classify an item. (*See e.g.*, Fig. 1, reference designator 108, p. 4, lines 25 - 29, p. 5, lines 7 - 11, p. 19, lines 21 - 25, p. 20, line 24 - p. 21, line 5, and, Fig. 7). The probabilistic dependency model contains dependencies on one or more classical outputs from a plurality of classifiers. (*See e.g.*, p. 6, line 13 - p. 6, line 28). The probabilistic dependence model further contains dependencies on one or more reliability indicators. (*See e.g.*, p. 2, line 25 - p. 3, line 2, p. 7, line 8 - p. 8, line 10).

C. Independent Claim 9

Independent claim 9 relates to a computer system comprising a first computer system component that learns, from training examples, probabilistic dependency models for classifying items according to one or more reliability indicators together with classical outputs from a plurality of classifiers. (*See e.g.*, p. 2, lines 22-24, Fig. 1, reference designator 106, p. 4, line 30 - p. 5, line 6, p. 6, lines 13 - 21, p. 6, line 29 - p. 8, line 10, Fig. 2, p. 14, line 9 - p. 15, line 27).

D. Independent Claim 14

Independent claim 14 is directed to a computer readable medium having computer executable instructions for performing steps comprising: implementing a plurality of classifiers adapted to receive and classify at least one item, the plurality of classifiers each generating a score related to classification of the at least one item; and, for each of one or more categories, facilitating classification, selection, and/or utilization of the at least one item with a probabilistic dependency model that employs one or more of the scores and, in addition, one or more reliability indicators. (*See e.g.*, p. 5, lines 15 - 24, p. 15, lines 16 - 18, p. 16, lines 8 - 9, p. 4, lines 25 - 29, p. 5, lines 7 - 11, p. 19, lines 21 - 25, p. 20, line 24 - p. 21, line 5, and, Fig. 7, p. 6, line 13 - p. 6, line 28, p. 6, line 29 – p. 7, line 7, p. 2, line 25 - p. 3, line 2, and, p. 7, line 8 - p. 8, line 10).

E. Independent Claim 16

Independent claim 16 relates to a system for classifying items that comprises means for determining a model that classifies the items based on a probabilistic approach that combines information about the items including one or more classical outputs of classifiers and one or more attributes of the items other than classical outputs of classifiers. (*See e.g.*, Fig. 1, reference designator 106, p. 4, line 24 - p. 5, line 6, p. 6, line 13 - p. 13, line 28, Fig. 2, p. 14, line 11 - p. 15, line 19). The system further comprises means for applying the model to classify the items. (*See e.g.*, Fig. 1, reference designator 108, p. 5, lines 7 - 14, p. 13, line 29 - p. 14, line 9, Fig. 3, p. 15, line 28 - p. 16, line 13, p. 19, lines 21 - 25).

The means for limitations described above are identified as limitations subject to the provisions of 36 U.S.C. §112 ¶6. The structures corresponding to these limitations are identified with reference to the specification and drawings in the above-noted parentheticals.

F. Independent Claim 17

Independent claim 17 is directed to a computer-readable medium having stored thereon a data structure useful in classifying items that comprises first data fields containing data representing an attribute to test, wherein the attributes represented include both classical classifier outputs and reliability indicators. (*See e.g.*, Fig. 4, p. 16, lines 14 - 26). The data structure further comprises second data fields corresponding to the first data fields and containing data representing values against which to compare the attributes. (*See e.g.*, Fig. 4, p. 16, line 26 - p. 17, line 2). Additionally, the data structure comprises third data fields containing data representing classifier outcomes. (*See e.g.*, Fig. 4, p. 17, lines 3-7). Finally, the data structure comprises fourth data fields facilitating determination of relationships among instances of the first, second, and third data fields, the relationships having a decision tree structure with the first and second data fields corresponding to decision nodes and the third data fields corresponding to leaf nodes. (*See e.g.*, Fig. 4, p. 17, lines 8-14).

G. Independent Claim 19

Independent claim 19 relates to a method of generating a classifier that comprises obtaining a set of training examples. (*See e.g.,* Fig. 2, reference designator 202, p. 14, lines 9 - 14). The method further comprises applying a probabilistic approach that uses the training examples to develop a model that combines evidence to provide an output relating to whether an item belongs in a category. (*See e.g.,*, Fig. 2, reference designator 204, p. 14, line 14 - p. 15, line 14). Next, the method comprises storing the model in a computer-readable media for use as a classifier (*See e.g.,* Fig. 2, reference designator 214, p. 15, lines 14 - 18). The method further provides the evidence comprises one or more classical outputs of other classifiers and one or more attributes of the item other than classical outputs of classifiers. (*See e.g.,* p. 2, line 19 - p. 3 line 2, p. 4, line 30 - p. 5, line 6, p. 13, line 29 - p. 14, line 8, and, p. 19, lines 16 - 20).

H. Independent Claim 24

Independent claim 24 is directed to a method of classifying items that comprises applying probabilistic dependency models, one for each of a plurality of categories, to an item stored in computer readable format to provide an output relating to whether the item belongs in the category with respect to each of the plurality of categories. (*See*, *e.g.*, Fig. 7, p. 20, line 24 - p. 21, line 5). The probabilistic dependency models collectively contain dependencies on outputs from a plurality of classifiers. (*See e.g.,* Fig. 1, p. 19, lines 16 - 25). The outputs considered by the probabilistic dependency models vary among the probabilistic dependency models. (*See e.g.,* p. 20, line 30 - p. 21, line 2).

I. Independent Claim 27

Independent claim 27 relates to a method of combining a plurality of classifiers to classify items that comprises sequentially applying tests to the items to obtain test results. (*See e.g.,* Fig. 5, p. 20, lines 3 - 15). The method further comprises classifying the items based on the test results. (*See e.g.,* Fig. 5, p. 20, lines 3 - 15). The sequence of tests applied varies among the items in that the outcome of one or more tests affects whether another test is applied, whereby the classifiers utilized vary depending on the items. (*See e.g.,* Fig. 5, p. 3, lines 7 - 9, p. 5, lines 2 - 4, p. 7, lines 26 - 29 and, p. 20, lines 3 - 15).

VI. Grounds of Rejection to be Reviewed (37 C.F.R. §41.37(c)(1)(vi))

A. Claims 1-28, 30 and 31 stand rejected as being unpatentable under 35 U.S.C. §102(e) over Gjerdingen *et al.* (US 6,539,395).

VII. Argument (37 C.F.R. §41.37(c)(1)(vii))

A. <u>Rejection of Claims 1-28, 30 and 31 Under 35 U.S.C. §102(e)</u>

Claims 1-28, 30 and 31 stand rejected under 35 U.S.C. §102(e) as being anticipated by Gjerdingen *et al.* (US 6,539,395). Reversal of this rejection is respectfully requested for at least the following reasons.

i. Gjerdingen et al. fails to teach or suggest each and every limitation set forth in the subject claims.

> A single prior art reference anticipates a patent claim only if it expressly or inherently describes each and every limitation set forth in the patent claim. *Trintec Industries, Inc. v. Top-U.S.A. Corp.,* 295 F.3d 1292, 63 USPQ2d 1597 (Fed. Cir. 2002); *See Verdegaal Bros. v. Union Oil Co. of California,* 814 F.2d 628, 631, 2 USPQ2d 1051, 1053 (Fed. Cir. 1987). The identical invention must be shown in as complete detail as is contained in the ... claim. *Richardson v. Suzuki Motor Co.,* 868 F.2d 1226, 9 USPQ2d 1913, 1920 (Fed. Cir. 1989) (emphasis added).

The subject invention generally relates to information management and in particular to a system and method for automatically classifying items. (p. 1, lines 6, 7). The invention provides meta-classifiers and systems and methods for building meta-classifiers. (p. 2, lines 17, 18). Meta-classifiers are combinations of multiple classifiers. (p. 1, lines 23, 24). A meta-classifier provides a determination or indication of whether an item belongs in a particular category. (p. 2, lines 18, 19). The meta-classifiers apply a probabilistic approach to combining evidence regarding correct classification of items. (p. 2, lines 19-21). Thus, meta-classifiers in accordance with applicants' invention take the form of probabilistic dependency models. (p. 2, lines 21, 22). Using a set of training data and machine learning

techniques, the probabilistic dependency models are constructed to effectively utilize evidence that can include outputs of multiple classifiers. (p. 2, lines 22-24). Additionally, the probabilistic dependency models of the invention can consider additional evidence, such as one or more reliability indicators. (p. 2, lines 25, 26).

To the contrary, Gjerdingen *et al.* discloses "[a] method for creating a database that allows content based searching in the music domain." *See* Abstract. Gjerdingen *et al.* employs feature vectors which are employed to compare music samples. (Col. 3, 18-20). The feature vectors of Gjerdingen *et al.* can include a vocal quality vector, a sound quality vector, a situational quality vector, a genre vector, an ensemble vector and an instrument vector. (Col. 12, line 21 – col. 14, line 35). A modeling module analyzes acquired data and performs a similarity computation. (Col. 15, lines 6, 7). The similarity computation determines the optimum function that can represent similarity between different music samples, based upon defined music attributes (i.e. feature vector values). (Col. 15, lines 6-11).

A function Fij represents the distances between music sample i and j and may be illustrated as:

$$WgDg + WeDe + WvDv + WtDt + WiDi$$

where Wg, We, Wv, Wt and Wi are individual weights allocated to individual music spaces. (Col. 16, lines 26 – 32). The plural weights Wg, We, Wt and Wi are calculated such that S1 and Fij are at a minimum distance from each other. (Col. 16, lines 32- 34).

Function Fij may be fit using linear regression or by nonlinear regression techniques. (Co. 16, lines 39, 40). Other tools may be used to compute the weights shown and fit function Fij: Bayesian estimation techniques, neural network techniques, classification trees and hierarchical clustering. (Col. 16, line 45 – Col. 17, line 21).

With regard to classification trees, Gjerdingen *et al.* discloses "[c]lassification trees define a hierarchical or recursive partition of a set based on the values of a set of variables." (Col. 17, lines 40 – 42). "In the present case, the variables are the elements of plural feature vectors." (Col. 17, lines 42, 43). "A decision tree is a procedure for classifying music into categories according to their feature vector values." (Col. 17, lines 43 – 45). "Expert pairwise data 403A may be used to define a satisfactory decision tree and then the tree may

be applied to a larger set of music." (Col. 17, lines 45 – 48). "This method partitions music samples into mutually exclusive categories, wherein music samples within each category are considered similar." (Col. 17, lines 48 – 50).

In the Advisory Action mail July 13, 2004, the Examiner asserts "[a] classification tree is a plurality of classifiers since the classification tree has a plurality of classifications." Advisory Action at p. 2. Applicants' representative respectfully submits that the Examiner's assertion is incorrect.

As set forth in MPEP §2111.01, words of the claims must be given their plain meaning unless applicant has provided a clear definition in the specification. *In re Zletz*, 893 F.2d 310, 321, 13 USPQ 2d 1320, 1322 (Fed. Cir. 1989). Further, claim terms are presumed to have the ordinary and customary meanings attributed to them by those skilled in the art. *Sunrace Roots Enter. Co. v. SRAM Corp.*, 336 F.3d 1298, 1302, 67 USPQ2d 1438, 1441 (Fed. Cir. 2003); *Brookhill-Wilk 1, LLC v Intuitive Surgical, Inc.*, 334 F.3d 1294, 1298, 67 USPQ2d 1132, 1136 (Fed. Cir. 2003). It is the use of the words in the context of the written description and customarily by those skilled in the relevant art that accurately reflects both the "ordinary" and the "customary" meanings of the terms in the claims. *Ferguson Beauregard/Logic Controls v. Mega Systems*, 350 F.3d 1327, 1338, 69 USPQ 2d 1001, 1009 (Fed. Cir. 2003).

As set forth in the specification of the subject application, a decision tree model is one example of a **classifier** – it is not a plurality of classifiers:

> There are many applications for automatic classification of items such as documents, images, and records. To address this need, a plethora of classifiers have been developed. Examples include a priori rule-based classifiers, such as expert systems, and classifiers based on probabilistic dependency models learned from trained data. Classifiers based on probabilistic dependency models include classifiers based on decision tree models, support vector machines, Bayesian belief networks, and neural networks.

p. 1, lines 10-16.

a. Independent claims 1 and 24

Independent claim 1 recites limitations of "a computer system component ***that applies probabilistic dependency models … wherein the probabilistic dependency models collectively employs outputs from a plurality of classifiers***". Similarly, independent claim 24 recites limitations of "***applying probabilistic dependency models … wherein the probabilistic dependency models collectively contain dependencies on outputs from a plurality of classifiers***." Gjerdingen *et al.* does not disclose employing the outputs of a plurality of classifiers to form a probabilistic dependency model.

Applicants' representative acknowledges that classifiers based on probabilistic dependency models include classifiers based on decision trees models, support vector machines, Bayesian belief networks, and neural networks (p. 1, lines 14-16). However, the disclosure of classifiers in Gjerdingen *et al.* is limited to computation of weights and function fitting. Gjerdingen *et al.* does not teach or suggest employing outputs from a plurality of classifiers to form the probabilistic classifier as set forth in independent claims 1 and 24.

Moreover, in the Final Office Action mailed April 5, 2004, the Examiner's states that "applicant does not claim 'the combination of a plurality of classifiers to form the probabilistic classifier'". (Final Office Action at p. 5). Such contention is without merit as independent claim 1 clearly recites the limitation of "***the probabilistic dependency models collectively employ outputs from a plurality of classifiers***", and, independent claim 24 recites "***applying probabilistic dependency models … wherein the probabilistic dependency models collectively contain dependencies on outputs from a plurality of classifiers***."

In view of at least the foregoing, it is readily apparent that Gjerdingen, *et al.* neither anticipates nor suggests the subject invention as recited in independent claims 1 and 24 (and claims 2, 3, 4, 25 and 26 which depend there from). Accordingly, this rejection should be reversed.

b. Independent claims 5, 9 and 14

Independent claim 5 is directed to a computer system for classifying items and recites a limitation of "a computer system component that applies a probabilistic dependency model to classify an item, wherein the probabilistic dependency model contains dependencies on one or more classical outputs from a plurality of classifiers and ***dependencies on one or***

more reliability indicators". (emphasis added).

Similarly, independent claim 9 is directed to computer system and recites a limitation of "a first computer system component that learns, from training examples, probabilistic dependency models for classifying items ***according to one or more reliability indicators*** together with classical outputs from a plurality of classifiers". Independent claim 14 is directed to a computer readable medium having computer executable instructions for performing steps comprising "implementing a plurality of classifiers adapted to receive and classify at least one item, the plurality of classifiers each generating a score related to classification of the at least one item; and for each of one or more categories, facilitating classification, selection, and/or utilization of the at least one item with a probabilistic dependency model that employs one or more of the scores and, in addition, ***one or more reliability indicators***". (Emphasis added).

"[R]eliability indicators are, in a broad sense, attributes of the items being classified." (p. 2, line 27). "These attributes can include characteristics of an item, source of an item, and meta-level outputs of classifiers applied to the item." (p. 2, lines 28, 29). "In general, a reliability indicator provides an indication of a classifier's reliability in classifying certain groups of items." (p. 2, line 29 – p. 3, line 1).

As discussed *supra*, Gjerdingen *et al.* does not disclose combining the outputs of a plurality of classifiers to form a probabilistic dependency model. Furthermore, Gjerdingen *et al.* does not disclose employment of reliability indicators with regard to the combination of the plurality of classifiers.

In the Final Office Action mailed April 5, 2004, the Examiner states that "applicant does not claim 'the combination of a plurality of classifiers to form the probabilistic classifier'". (Final Office Action at p. 6). The Examiner's position is incorrect. Independent claim 5 includes the limitation "***the probabilistic dependency model contains dependencies on one or more classical outputs from a plurality of classifiers and dependencies on one or more reliability indicators***". Similarly, independent claim 9 is directed to computer system and recites a limitation "a first computer system component that learns, from training examples, probabilistic dependency models for classifying items according to one or more reliability indicators together with ***classical outputs from a plurality of classifiers***". (Emphasis added). Finally, independent claim 14 is directed to a computer readable medium

having computer executable instructions for performing steps comprising "***implementing a plurality of classifiers*** adapted to receive and classify at least one item…" (Emphasis added).

In view of at least the above, it is readily apparent that Gjerdingen, *et al.* neither anticipates nor suggests the subject invention as recited in independent claims 5, 9 and 14 (and claims 6, 7, 8, 10, 11, 12, 13, 15 and 30 which depend there from). Accordingly, this rejection should be reversed.

c. Independent claim 16

Independent claim 16 is directed to a system for classifying items and recites "means for determining a model that classifies the items based on a probabilistic approach that combines information about the items including ***one or more classical outputs of classifiers and one or more attributes of the items other than classical outputs of classifiers***". (Emphasis added).

In the Final Office Action mailed April 5, 2004, the Examiner asserts that:

> To one of ordinary skill in the art, a classification tree will combine information about the items including one or more classical outputs of classifiers and one or more attributes of the items other than classical outputs of classifiers. The classification tree has various classifications and various nodes that are combined. The tree is the model.

Final Office Action at p. 7.

As noted *supra*, a decision tree model is one example of a **classifier** – it is not a plurality of classifiers. (p. 1, lines 10-16). Accordingly, the Examiner's contention is not correct. Gjerdingen *et al.* does not disclose employing the outputs of a plurality of classifiers to form a model. Furthermore, Gjerdingen *et al.* does not disclose employment of attributes with regard to the combination of the plurality of classifiers.

It is readily apparent that Gjerdingen, *et al.* neither anticipates nor suggests the subject invention as recited in independent claim 16. Accordingly, this rejection should be reversed.

d. Independent claim 17

Independent claim 17 is directed to a computer-readable medium having stored thereon a data structure useful in classifying items and recites:

> first data fields containing data representing an attribute to test, wherein the attributes represented include both classical classifier outputs and reliability indicators;
>
> second data fields corresponding to the first data fields and containing data representing values against which to compare the attributes;
>
> third data fields containing data representing classifier outcomes;
>
> fourth data fields facilitating determination of relationships among instances of the first, second, and third data fields, the relationships having a decision tree structure with the first and second data fields corresponding to decision nodes and the third data fields corresponding to leaf nodes.

As discussed previously, Gjerdingen *et al.* does not disclose employing classifier outputs and reliability indicators to classify items.

In the Final Office Action mailed April 5, 2004, the Examiner states "application does not claim 'combination classifier outputs and reliability indicators to classify items'". Final Office Action at p. 8. The Examiner's position is without merit as independent claim 17 includes the limitation of "wherein the attributes represented include ***both classical classifier outputs and reliability indicators***". (Emphasis added).

In view of at least the above, it is clear that Gjerdingen, *et al.* neither anticipates nor suggests the subject invention as recited in independent claims 17 (and claim 18 which depends there from). Accordingly, this rejection should be reversed.

e. Independent claim 19

Independent claim 19 is directed to a method of generating a classifier and recites a limitation of "applying a probabilistic approach that uses the training examples to develop a model that combines evidence to provide an output relating to whether an item belongs in a category ... ***wherein the evidence comprises one or more classical outputs of other classifiers and one or more attributes of the item other than the classical outputs of classifiers***". (Emphasis added). Gjerdingen *et al.* does not disclose the employment of classifier outputs and attributes to classify items as in applicants' invention as recited in the subject claim.

In the Final Office Action mailed April 5, 2004, the Examiner asserts that:

> To one of ordinary skill in the art, a classification tree will combine information about the items including one or more classical outputs of classifiers and one or more attributes of the items other than classical outputs of classifiers. The classification tree has various classifications and various nodes that are combined. The tree is the model.

Final Office Action at p. 8.

As noted previously, as set forth in the specification of the subject application, a decision tree model is one example of a **classifier** – it is not a plurality of classifiers. (p. 1, lines 10-16). Accordingly, the Examiner's position is without merit.

In view of at least the above, it is readily apparent that Gjerdingen, *et al.* neither anticipates nor suggests the subject invention as recited in independent claim 19 (and claims 20, 21, 22 and 23 which depend there from). Accordingly, this rejection should be reversed.

f. Independent claim 27

Independent claim 27 is directed to a method of combining a plurality of classifiers to classify items and recites a limitation of "sequentially applying tests to the items to obtain test results... ***wherein the sequence of tests applied varies among the items in that the outcome of one or more tests affects whether another test is applied, whereby the***

classifiers utilized vary depending on the items." (Emphasis added). Gjerdingen *et al.* does not disclose or suggest one or more tests affecting whether another test is applied as in the subject claimed invention.

In the Final Office Action mailed April 4, 2004, the Examiner states "applicant does not claim in the body of the claim 'combination classifier outputs and reliability indicators to classify items.'" Final Office Action at p. 9. This is clearly incorrect - independent claim 27 recites the limitation of "wherein the sequence of tests applied varies among the items in that the outcome of one or more tests affects whether another test is applied, whereby ***the classifiers utilized vary depending on the items***". (Emphasis added).

Gjerdingen, *et al.* neither anticipates nor suggests the subject invention as recited in independent claims 27 (and claim 28 which depends there from). Accordingly, this rejection should be reversed.

B. Conclusion

For at least the above reasons, the claims currently under consideration are believed to be patentable over the cited references. Accordingly, it is respectfully requested that the rejections of claims 1-28, 30 and 31 be reversed.

If any additional fees are due in connection with this document, the Commissioner is authorized to charge those fees to Deposit Account No. 50-1063 (Reference No. MSFTP217US).

Respectfully submitted,
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VIII. Claims Appendix (37 C.F.R. §41.37(c)(1)(viii))

1. A computer system for classifying items, comprising:

a computer system component that applies probabilistic dependency models, one for each of a plurality of categories, to an item to provide with respect to each of the plurality of categories an indication of whether the item belongs;

wherein the probabilistic dependency models collectively employ outputs from a plurality of classifiers; and

the outputs employed by the probabilistic dependency models vary among the probabilistic dependency models.

2. The computer system of claim 1, wherein the dependency models collectively employ one or more reliability indicators.

3. The computer system of claim 1, wherein the probabilistic dependency models are decision trees.

4. The computer system of claim 1, wherein the items are texts.

5. A computer system for classifying items, comprising:

a computer system component that applies a probabilistic dependency model to classify an item, wherein the probabilistic dependency model contains dependencies on one or more classical outputs from a plurality of classifiers and dependencies on one or more reliability indicators.

6. The computer system of claim 5, wherein the computer system outputs a quantitative measure relating to confidence that the item belongs in a category.

7. The computer system of claim 6, wherein the probabilistic dependency models are decision trees.

8. The computer system of claim 6, wherein the items are texts.

9. A computer system, comprising:

a first computer system component that learns, from training examples, probabilistic dependency models for classifying items according to one or more reliability indicators together with classical outputs from a plurality of classifiers.

10. The computer system of claim 9, further comprising a second computer system component that repeatedly invokes the first component to learn probabilistic dependency models employing various potentially effective reliability indicators and compares the performances of the resulting probabilistic dependency models to identify reliability indicators that are effective.

11. The computer system of claim 9, wherein the first computer system component employs the classical outputs from classifiers and the reliability indicators in the same manner.

12. The computer system of claim 9, wherein the probabilistic dependency models are decision trees.

13. The computer system of claim 9, wherein the items are texts.

14. A computer readable medium having computer executable instructions for performing steps comprising:

implementing a plurality of classifiers adapted to receive and classify at least one item, the plurality of classifiers each generating a score related to classification of the at least one item; and

for each of one or more categories, facilitating classification, selection, and/or utilization of the at least one item with a probabilistic dependency model that employs one or more of the scores and, in addition, one or more reliability indicators.

15. The computer readable medium of claim 14, wherein:

the instructions implement a different probabilistic dependency model for each of two or more categories;

the probabilistic dependency models are based on subsets of parameters selected from the group consisting of the scores and the reliability indicators; and

the subsets of parameters vary among the probabilistic dependency models.

16. A system for classifying items, comprising:

means for determining a model that classifies the items based on a probabilistic approach that combines information about the items including one or more classical outputs of classifiers and one or more attributes of the items other than classical outputs of classifiers; and

means for applying the model to classify the items.

17. A computer-readable medium having stored thereon a data structure useful in classifying items, comprising:

first data fields containing data representing an attribute to test, wherein the attributes represented include both classical classifier outputs and reliability indicators;

second data fields corresponding to the first data fields and containing data representing values against which to compare the attributes;

third data fields containing data representing classifier outcomes;

fourth data fields facilitating determination of relationships among instances of the first, second, and third data fields, the relationships having a decision tree structure with the first and second data fields corresponding to decision nodes and the third data fields corresponding to leaf nodes.

18. The computer-readable medium of claim 18, wherein the data represented by the first data fields comprises classical classifier outputs from a plurality of classifiers.

19. A method of generating a classifier, comprising:

obtaining a set of training examples;

applying a probabilistic approach that uses the training examples to develop a model that combines evidence to provide an output relating to whether an item belongs in a category; and

storing the model in a computer-readable media for use as a classifier;

wherein the evidence comprises one or more classical outputs of other classifiers and one or more attributes of the item other than classical outputs of classifiers.

20. A method of identifying useful reliability indicators, comprising

obtaining potentially useful reliability indicators;

applying the method of claim 19 using various of the potentially useful reliability indicators as evidence; and

comparing the resulting classifiers to identify which of the potentially useful reliability indicators are, in fact, useful.

21. The method of claim 19, wherein the model is a decision tree.

22. The method of claim 19, wherein the evidence comprises classical outputs from two or more classifiers.

23. A method of classifying items, comprising:

obtaining the items in computer readable format,

employing a computer to classify the item using a classifier generated according to the method of claim 19.

24. A method of classifying items, comprising:

applying probabilistic dependency models, one for each of a plurality of categories, to an item stored in computer readable format to provide an output relating to

whether the item belongs in the category with respect to each of the plurality of categories;

wherein the probabilistic dependency models collectively contain dependencies on outputs from a plurality of classifiers; and

the outputs considered by the probabilistic dependency models vary among the probabilistic dependency models.

25. The method of claim 24, wherein the dependency models collectively contain dependencies based on one or more reliability indicators.

26. The method of claim 24, wherein the probabilistic dependency models are decision trees.

27. A method of combining a plurality of classifiers to classify items, comprising:

sequentially applying tests to the items to obtain test results; and

classifying the items based on the test results.

wherein the sequence of tests applied varies among the items in that the outcome of one or more tests affects whether another test is applied, whereby the classifiers utilized vary depending on the items.

28. The method of claim 27, wherein one or more of the tests involves a reliability indicator.

29. Withdrawn

30. The computer system of claim 10, wherein the second component automatically selects the potentially effective reliability indicators.

31. The method of claim 23, wherein the items are texts.

IX. Evidence Appendix (37 C.F.R. §41.37(c)(1)(ix))

None.

X. Related Proceedings Appendix (37 C.F.R. §41.37(c)(1)(x))

None.